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RNN-LSTM Applied in a Temperature Prediction Model for Greenhouses

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Abstract. The climatic variables in protected agriculture are essential factors for the plant growth and, in general, of the entire crop. A good forecast of variables such as the internal temperature could help farmers to prevent losses in the harvest. In the present paper, the temperature forecast inside a greenhouse is obtained by implementing Deep Learning tools. The topology used for the temperature forecast was Recurrent Neural Networks (RNN) with Long-Short Term Memory (LSTM) algorithm. It is a type of neural network known to be suitable for processing time-series data. The analysis is performed with the many to one configuration for three input elements and one output element. The metrics used for the data analysis and validation (RMSE, MAE, R^2, and C_{eff}); it was observed that they significantly improve when the internal temperature is incorporated as part of the input elements in the combinations for forecasting. The results obtained with the RNN-LSTM provide RMSE values less than 0.30 and R^2 greater than 0.90, with a forecast interval of one hour into the future for Internal Temperature. It is shown that the LSTM algorithm within the RNN is an effective tool for a good forecast in time series, significantly helping the forecast of climatic variables in protected agriculture.

Keywords: RNN-LSTM, temperature prediction, deep learning.

1 Introduction

A good of climatic variables is essential for outstanding management in agriculture, either in the open air or in greenhouses. Therefore, a correct action that helps the observation and reasonable interpretation of the variables is through monitoring [1].

In the fourth industrial revolution, digital technology is made from integrating data and the connection of resources, creating an efficient and sustainable.

It has a presence in the agricultural world by implementing Intelligent components, creating interconnection of systems and machines. Its main objective is to have better production systems through the adaptability of monitoring and control systems, increasing the efficiency of production systems, fundamentally by optimizing energy consumption, machinery automatic control, water usage, fertilizers, and phytosanitary products, giving rise to what has been called Precision Agriculture [29]. Agriculture 4.0 uses technologies such as the Internet of Things, Big Data, Artificial Intelligence, Embedded Systems, Cloud Computing, Remote Sensing, among others, part of Industry 4.0.

Applications of these technologies can significantly improve the efficiency of agricultural activities [24, 25, 26]. Low-cost sensors and actuators can now connect to network platforms and upload their data to a remote database where Big Data analysis can occur. These network platforms aim to optimize the production efficiency, increasing quality, minimizing environmental impacts, and reducing the use of resources such as energy, water, and other consumables [27, 28] conducted a survey on the application of Big Data to agriculture.

They have pointed out that Big Data is now used to provide farmers with predictive insights in agricultural operations and operational decisions in real-time from monitoring by implementing artificial intelligence as a prediction system. Miranda et al. [4] mention the great importance of carrying out effective monitoring of the climatological variables of interest. In the present investigation, monitoring is carried out considering the variables of most significant interest for the study to make an efficient prediction of the internal temperature, to anticipate the appearance of possible problems in the culture [5].

The monitoring carried out in this research is carried out using advanced computational tools and since, in present investigations, strategies have been carried out through Artificial Intelligence (AI) to detect levels of interest in the behavior of the variables, guaranteeing the control and efficiency in crop productivity. [6]. Recurrent Neural Networks (RNN) are one of the AI topologies that have been used in recent years with acceptable results for the prediction of time series. RNN functions accurately as an identifier of trends for data and patterns are suitable for forecasting applications such as Deep Learning (DL) [2].

Jha et al. [8] show the RNN supplemented with the Long-Short Term Memory (LSTM) algorithm as predictors with levels of reliable precision if fed with a significant set of variables of interest for the prediction of time series in forecasting models for greenhouses. Jung et. al [9] as well as Hongkang et. al [10] propose models based on RNN with LSTM (RNN-LSTM) algorithms [11]. Gharghory [11] uses metrics such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of variance to evaluate the prediction precision of an RNN-LSTM model and compare it to other models [3].

In this study, an approach to forecasting the internal temperature of a greenhouse is developed using external and internal climate data captured for a given period by a weather station and sensors connected to it.

Different RNN-LSTM structures configured through hyperparameters of interest were trained and tested with collected data. All RNN-LSTM were evaluated with metrics suggested in [11] and compared with different forecast approaches to assess the goodness and suitability of this approach for the greenhouse internal temperature forecasting.

The LSTM algorithm has a significant advantage in expanding the memory capacity of the neural network. This characteristic leads to keeping a vast set of background data as a reference for the forecasting system. Keeping a large amount of data can significantly impact the accuracy of the prediction, reducing the RMSE and MAE to 0.5 and 0.004, respectively [2].

2 Related Works

Numerous investigations have been carried out with the objective of forecasting temperature, humidity, solar radiation, and other variables within protected environments such as greenhouses. All these are to determine the growth behavior of the crop [9]. There are several forecasting models.

However, in recent years' predictors based on Artificial Neural Networks have gained importance due to the range of tools provided by Machine Learning and the structures of algorithms. Dae-Hyun et al. [9] show comparisons between different structures considering various learning algorithms for the time series prediction. Abdulkarim et al. [11] show the advantage of the RNN, which can feedback the neuron output signal to the same neuron in the next time step.

The metrics usually used to assess LSTM prediction performance are the mean square error (MSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the square root of the mean square error (RMSE), and the Nash-Sutcliffe coefficient of efficiency (NSCE) [9, 11]. The LSTM algorithm has a significant advantage in expanding the memory capacity of the neural network. This characteristic leads to keeping a vast set of background data as a reference for the forecasting system. Keeping a large amount of data can significantly impact the accuracy of the prediction, reducing the RMSE and MAE to 0.5 and 0.004, respectively [2]. Singh [16] implements the RNN-LSTM to work with time series to forecast the Temperature and Relative Humidity inside a greenhouse.

For the temperature model, the metrics implemented for its validation were the MAE, RMSE, and R^2, obtaining MAE values of 0.488 for the temperature forecast, guaranteeing that the reliability of the forecast is within ±1°C. The RMSE obtained is 0.865, and the coefficient of determination R^2 is 0.953, which indicates that the general dispersion is small and does not cause a significant error with the observed temperature.

The RNN-LSTM training datasets can be selected in two ways. One way can be with 90% of the data sequence and the remaining 10% for testing and validation of the network. The other way is with 80% of the data sequence for training and the remaining 20% for network testing and validation. All the data must be normalized [3].

3 Methodology

The present research work presents new contributions for forecasting the green-house internal temperature using RNN and Deep Learning, using the Long Short-Term

Table 1. Climate Variables considered for this study.

Nomenclature	Climate Variable	Units
Ti	Internal Temperature	°C
To	External Temperature	°C
Ho	External Humidity	%
Hi	Internal Humidity	%
Di	Dew Point	%
Rs	Solar Radiation	W/m²

Fig. 1. Davis Vantage Pro 2 Weather Station.

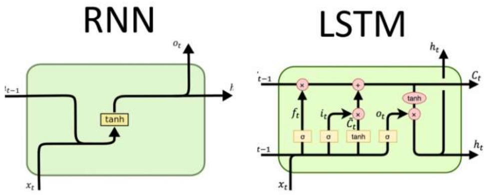


Fig 2. Data flow at time step t, Copyright 2020 by MathWorks Inc.

Memory (LSTM) algorithm as the one presented by Hochreiter and Schmidhuber in 1997 [17].

The data collection of the climatic variables was carried out inside (Internal Temperature and Relative Humidity) and outside (External Relative Humidity, Solar Radiation, Outdoor Temperature, Wind Direction, and Wind Speed) a greenhouse (Table 1), using a Davis Vantage Pro2 meteorological station (Fig.1).

The greenhouse has a curved roof (165m2in area, 27.5 m long, 6 m wide) and plastic cover. It is traditionally used without any climate control equipment inside and relies only on natural ventilation.

The greenhouse is in the Mezquitera Sur, Juchipila, Zacatecas, Mexico. The data collection was carried out from July 12, 2020, to November 6, 2020, with a 5-minute sampling time for all the climatic variables of interest. A total of 33,696 samples were recorded for training and testing of the RNN-LSTM.

The RNN-LSTM topology is based on a generalization of the feedforward neural network that has internal memory. RNN is recurrent at the neuron level as the neuron output is calculated using the current inputs and its previous output. The RNN considers the current inputs and the output that it has learned from the before deciding.

Table 2. Components of the data flow over time t.

Nomenclature	Definition	Formula
i_t	Input Gate	$i_t = \sigma(W_i x_t + R_i h_{t-1} + b_i)$
f_t	Forgate Gate	$f_t = \sigma\left(W_f x_t + R_f h_{t-1} + b_f\right)$
C_t	Cell candidate	$C_t = \tanh\left(W_g x_t + R_g h_{t-1} + b_g\right)$
O_t	Ouput Gate	$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o)$

Table 3. Hyperparameter settings sets.

Parameter	Value 1	Value 2	Value 3	Value 4	Value 5	Value 6	Value 7
Input Size	3	3	3	3	3	3	3
Number of Rsponses	1	1	1	1	1	1	1
Hidden Units	2	2	1	1	1	1	1
Number of Epochs	200	250	300	300	300	350	300
Mini Batch Size	720	650	620	620	620	800	700
Gradient Threshold	0.9	0.5	0.6	0.8	0.9	0.6	0.7
Learning Rate	0.02	0.1	0.001	0.005	0.001	0.002	0.005
Learn Rate Schedule	150	200	200	125	125	120	200
Learn Rate drop Factor	0.5	0.2	0.2	0.2	0.2	0.3	0.5
Number of hiden units	100	200	250	250	300	350	400

The ADAM algorithm was adopted to make the calculation of the LSTM network more efficient. The architecture of the RNN-LSTM is observed in Fig. 2. The behavior of the data flow over time t is shown in Table 2.
where **σ** is the sigmoid activation function for the entry, forgetting, and exit gates respectively, the activation function **tanh** for the candidate gate, **W** the vector of weights for the entry, forgetting, and exit gates respectively, the function activation **tanh** for the candidate gate, **R** is the vector of recurring weights for the entry, forgetting, candidate and exit gates, **ht-1** is the output of the previous cell and **b** is the bias vector for the entry gates, oblivion, candidate and exit respectively. The most important things to consider when training and testing Neural Networks containing the LSTM algorithm are hyperparameters. These can affect its precision and performance [18, 19, 9, 20].

In Table 3, all the hyperparameters to be considered are shown. For this type of network, the most important are:

- Learning rate,
- Number of units of the hidden layer and,
- Mini Batch Size [14].

The number of units in the hidden layer will influence the adjustment effect. If the Mini batch size is too small, the training data will be challenging to converge, leading to a mismatch. Many consulted papers start with a high learning rate and lower it as the training goes on. We noted that the learning rate is very dependent on the network architecture. If the learning rate is too large, the required memory will increase

Table 4. Metrics for the evaluation of the efficiency of the RNN-LSTM.

Evaluation	RMSE	C_{eff}
Very Good	≤ 0.30	≥ 0.91
Good	0.30-0.40	0.84 - 0.91
Acceptable	0.40-0.50	0.75 - 0.84
No Acceptable	> 0.50	< 0.75

significantly [11]. The experimental environment consisted of an Intel (R) Core (TM) i5-9300H2.40 GHz quad-core processor with a 16 GB memory. The operating system was Windows 10 64-bit; the programming was carried out in MATLAB software.

The various structures were obtained from the hyperparameters variation. Table 3 shows the different hyperparameter settings used for this work. The criteria for evaluating the goodness and suitability of the network based on the fit are shown in Table 4 [21]. The MAE is used to reflect prediction errors, and its range is [0, +∞). When the predicted and observed values are identical, the MAE is zero, indicating a perfect model. Significant errors lead to high MAE values [22].

Other metrics to consider in the analysis to check the goodness of the network are the coefficient of determination (R^2) and the Coefficient of efficiency (C_{eff}) that help determine the closeness of the predicted data with the observed data. Both coefficients range is [0, 1], [9, 21]. The number of combinations made was obtained from five variables of interest; the internal temperature was excluded, in arrays of 3 input elements through formula 1:

$$C_r^n = \frac{n!}{(n-r)!\,r!}, \tag{1}$$

where:

n = Total climatic variables considered.

r = Number of variables considered for each arrangement.

From this, a total of 10 combinations were obtained to perform the tests with the RNN-LSTM. The metrics analyzed were the Mean Square Error (RMSE), the Absolute Mean Error (MAE) [3], and the Determination Coefficient (R^2) [23].

Later, seeking to improve the prediction results for the internal temperature (T_i), the five inputs combinations with best RMSE and C_{eff} were selected, and one input variable in each combination was substituted with the internal temperature, generating new input combinations.

The RNN-LSTM was trained and tested with the 80-20 arrangement, 80%training data, and 20% test data. The metrics analyzed were the Mean Square Error (RMSE), the Absolute Mean Error (MAE) [3], and the Determination Coefficient (R^2) [23].

4 Results

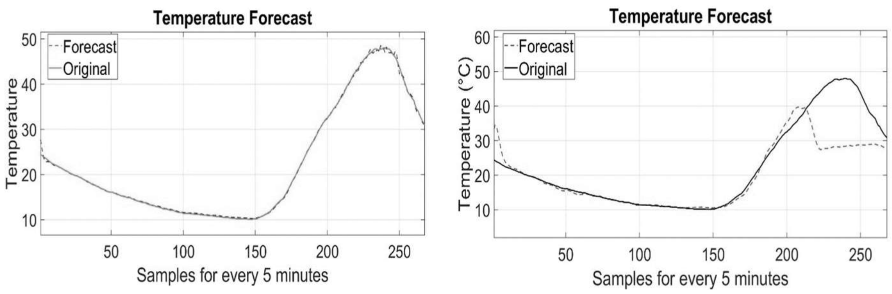
The best results for the RNN-LSTM training and testing were achieved with the hyperparameters set shown in column Value 4 of Table 3. These results were validated using the metrics shown in Table 5 and Table 6. The RMSE values shown in Table 5 have a range from 0.30027 to 5.5629.Fig. 3a, shows the forecast vs. actual value of an

Table 5. Sequence of input-output variables (Many to one).

put Secuence	RMSE	MAE	R^2	C_{eff}
Hi-Id-Rs	0.3003	0.0095	0.9994	0.9
Hi-Id-To	0.3128	0.0123	0.9993	0.9
Hi-Id-Ho	0.3966	0.0099	0.9989	0.9
Id-Rs-Ho	1.4368	0.0471	0.9857	0.9
Hi-Ho-To	1.8531	0.0451	0.9762	0.9
Id-Ho-To	3.3477	0.0721	0.9223	0.9
Hi-To-Rs	3.4352	0.0783	0.9182	0.9
Id-Rs-To	4.2746	0.0730	0.8734	0.8
Ho-To-Rs	5.3143	0.0853	0.8043	0.8
Hi-Rs-Ho	5.5629	0.3228	0.7856	0.7

Table 6. Comparison of data obtained in the different training sequences (Many to one).

Input Secuence	RMSE	MAE	R^2	C_{eff}
Hi-Id-Ti	0.1493	0.00407	0.9998	0.9998
Ho-To-Ti	0.1876	0.0077	0.9998	0.9998
Hi-Ti-To	0.2081	0.0075	0.9997	0.9997
Hi-Ho-Ti	0.2118	0.0059	0.9997	0.9997
Id-Rs-Ti	0.2507	0.0127	0.9996	0.9996



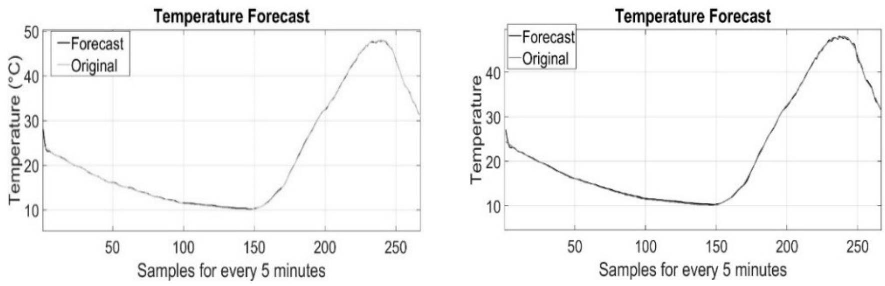
(a) (b)

Fig. 3. Behavior curves of the temperature forecast first sequence of input variables.

RNN-LSTM with 0.3 RMSE, while Fig. 3b, shows the forecast vs. actual value of an RNN-LSTM with 5.5629RMSE. As for the MAE values from 0.0095 to 0.32. For theR2coefficient, the range of values was 0.7856 to 0.9994, and C_{eff} values from 0.9994 to 0.7970. Subsequently, a new training pattern for the RNN-LSTM using the internal temperature (T_i) within the input sequence as shown in the following Table 6 was tried out. The results obtained had RMSE values from 0.14931 to 0.2507, MAE values from 0.00407 to 0.0127, and R^2up to 0.9998, and C_{eff} under to 0.2507, which presents a solid test forecast relationship.

Table 7. Comparison of parameters obtained.

Implemented model	RMSE	MAE	R^2	C_{eff}
Hi-Id-Ti	0.1493	0.00407	0.9998	0.9998
Ho-To-Ti	0.1876	0.0077	0.9998	0.9998
Hi-Ti-To	0.2081	0.0075	0.9997	0.9997
Hi-Ho-Ti	0.2118	0.0059	0.9997	0.9997
Id-Rs-Ti	0.2507	0.0127	0.9996	0.9996
[32] (RNN)	1.7963	1.3431	–	–
[32] (LSTM)	1.8044	1.3521	–	–
[32] (EEMD-LSTM)	0.7098	0.5336	–	–
[33] (RNN)	0.865	0.488	0.953	–
[31] (MLP-BPP)	0.711	0.558	0.980	–
[30] (CFD)	2.3518	2.0312	–	–



(a) (b)

Fig. 4. Behavior curves of the temperature forecast, second sequence of input variables.

The forecast graphs (Fig. 4a and Fig. 4b) show the similarities and slight differences between forecast and actual values. The prediction model makes forecasts very close to the observed values. From the metrics obtained, it was observed that the five sequences that contain T_i yielded good forecast results of the greenhouse internal temperature. In Table 7 a comparison of statistical metrics between this work and others found in the literature for the same application is shown.

5 Conclusions

The obtained results show that the combination of RNN-LSTM algorithms and a good selection of input variables can yield outstanding forecasting results. Metrics values such as RMSE = 0.1493 and C_{eff}= 0.9998 were obtained, which are considered by the literature as very good for the behavior of the RNN with LSTM algorithm. It is also observed that the predicted values and the observed values are very close.

This is corroborated by the values of the coefficient of determination R^2 with results of 0.9998, and the MAE = 0.00407. These metrics values were achieved thanks to the relationship that exists between the internal dew (Id), internal relative humidity (Hi), and the internal temperature (Ti)variables in the greenhouse.

The applied model of RNN-LSTM has proven to be a tool that generates a clear interpretation of the training data. With a somewhat limited amount of data of 33,696, 80% of the data was enough to provide a model with excellent metrics when forecasting the greenhouse's internal temperature.

Future work is considered to make other prediction models using alternative ANN topologies such as Convolutional Neural Networks with Long-Short Term Memory algorithm (CNN-LSTM) and Support Vector Regression (SVR). This work will allow a fair comparison for these topologies when they are applied to this application.

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